



Artificial Neural Network Assisted Mitigation of Cross-modulation Distortion in Microwave Photonics Link

Yihui Yin¹, Wanli Yang¹(✉), Xu Yang², Yong Qin¹, and Hongtao Zhu¹

¹ The 34th Research Institute of China Electronics Technology Group Corporation, Guilin 541004, China

² The 54th Research Institute of China Electronics Technology Group Corporation, Shijiazhuang 050081, China

Abstract. A multi-carrier down-conversion microwave photonics link (MDC-MWPL) is designed to deliver the broadband radio frequency (RF) signals with multiple frequency and down-conversion the RF signal to intermediate frequency (IF) signal, contributing to the wide bandwidth, low loss, strong immunity to electromagnetic interference property of microwave photonics link. However, the link performance is often degraded by the cross-modulation distortion (XMD). So, a kind of artificial neural network genetic algorithm (ANN-GA) distortion compensation technique is proposed to mitigate the XMD of the MDC-MWPL. The trained artificial neural network fits the input-to-output mapping of the link and predicts the link output. Taking the predicted output as the individual fitness value of the genetic algorithm, the optimal compensation factor γ is found. Taking advantage of the γ , the XMD is mitigated by extracted and reconstructed compensation signal, with a suppression ratio of -65 dB. Different from the traditional digital distortion compensation method, the proposed technique can realize distortion compensation for any kinds of links, which is not limited to a fixed microwave photonics link and its mathematical model, improving the intelligence and flexibility of microwave photonic link linearization design.

Keywords: Microwave photonics · Cross modulation distortion · Artificial neural network · Genetic algorithm

1 Introduction

As the RF bandwidth of communication and radar applications continues to grow, the transmission, processing, and reception of the ultra-broadband, multi-carrier RF signal are difficult to be conducted by traditional electrical technology. The rapid development of photonic technology has made people realize that photonic technology will become a prospective analogue signal processing platform. Combining the microwave and photonics, contributing to its wide bandwidth, low loss, strong immunity to electromagnetic interference property, the microwave photonics technology addresses the

processing capabilities of the complex RF signals in conventional microwave systems. In recent years, significant progress has been made in the design of single carrier or multiple carrier RF Over Fiber link (ROF) and down-conversion microwave photonics link. To obtain the high sensitivity, large dynamic range link property, many kinds of linear techniques are proposed. Linearity in RF photonic links is frequently limited by the modulator response. In a conventional narrow-band link where the third-order inter modulation distortion (IMD3) dominates, the linearization has been demonstrated by several designs, such as cascaded or parallel electro-optic modulators [1, 2], in which, an MZM operating at the opposite slopes of the transfer functions, or a pair of parallel MZMs operating at opposite slopes of the transfer functions. In addition, electronic pre-distortion [3, 4], feed-forward compensation [5, 6], and post digital signal compensation [7, 8] are also important means. However, in a channelized RF photonic link, where the input RF signal is broadband with multiple frequency components, the link linearity is not only distorted by IMD3, but also impacted by cross-modulation distortion (XMD). In [9], the XMD is suppressed by pre-distortion. In [10], the XMD is mitigated through post-digital-distortion compensation. For the digital distortion compensation, the most of XMD suppression methods are based on the small signal model, which are failed when the modulation depth is deep.

Artificial intelligence microwave photonics technique is an emerging direction in microwave photonics. The Artificial Neural Networks (ANNS) originated in 1943, and has developed for more than half a century. The ANNS has made tremendous progress contributing to the ability of self-study, associate storage, high-speed search for the best solutions, and drawing arbitrarily complex nonlinear relationships. In recent years, the ANN has been applied in the field of optoelectronics to enhance the system performance [11–13]. A microwave photonics link is mathematically viewed as a nonlinear function with specifying the input output variables. Thus, by training the ANNS with input and output data of the microwave photonics link, the ANNS enables the fitting of the input-to-output nonlinear mapping of the microwave photonics link. Then, the trained ANNS can predict the output of the microwave photonics link with the given input.

Taking advantage of the traditional digital distortion compensation method, based on the artificial neural network genetic algorithm (ANN-GA), a kind of ANN-GA based distortion compensation technique is proposed for multi-carrier down-conversion microwave photonics link (MDC-MWPL). The link structure consists of a laser, modulators, a photodiode (PD), an analog digital converter (ADC) module, a digital signal process (DSP) module, and a ANN-GA module. In the ADC and DSP modules, compensation signal is extracted and reconstructed using the compensation factor γ . The γ is given by the ANN-GA module. In the ANN-GA module, the artificial neural networks learn and predict the input-to-output mapping of the link, and give a predicted output value as the fitness value of the genetic algorithm. Based on the fitness value, the genetic algorithm found the optimal compensation factor γ . Thus, extracted compensation signal is multiplied by the appropriate compensation factor γ , and fed back to the link to eliminate the XMD with a suppression ratio great than -65 dB.

2 Principle of the ANN-GA Distortion Compensation Technique

2.1 Principle of XMD Compensation for MDC-MWPL

The MDC-MWPL structure, shown in the Fig. 1(a), consists of a laser, two modulators (one for the modulation of broadband multi-carrier signals and the other for down-conversion the target carriers), a photoelectric detector, the ADC module, the DSP module, and the ANN-GA module. The broadband multi-radio carrier RF signals are modulated on the optical carrier in the modulator 1. The polarization controller is used to adjust the polarization state of the output optical carrier, keeping the polarization state of the light carrier into the modulator 1 to be consistent with the modulator spindle. The modulated output light signal is then modulated by a local oscillator (LO) signal in the modulator 2 operating at the orthogonal bias point to down-convert the RF signal to the IF signal. The IF signal is recovered by low-speed PD. The recovered signal is sampled by the ADC module and converted to digital signal. Within the digital domain, by using a narrow band digital filter, the signal is further divided into two sections, denoted by signal 1 (S_1) and 2 (S_2), respectively, and the two signals are used to construct a compensation signal to suppress the XMD. The DSP process is shown in Fig. 1(b).

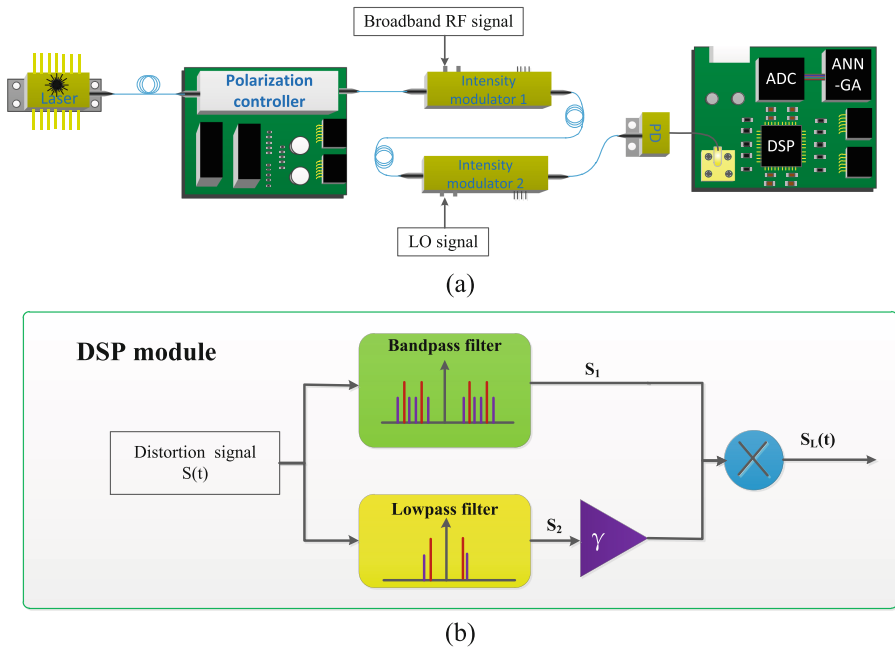


Fig. 1. (a) The multi-carrier down-conversion microwave photonics link, (b) the diagram of the DSP process for reconstructing the compensation signal.

To explain the XMD compensation mechanism, the compensation process is expressed by the mathematical form. Mathematically, the modulated broadband multi-carrier RF signal, denoted as $x(t)$, can be written as Eq. (1), which is expressed as a center frequency of ω_n with amplitude of $A_n(t)$ and the phase of $\phi_n(t)$.

$$x(t) = \sum_n A_n(t) \cos(\omega_n t + \phi_n(t)) \quad (1)$$

For an intensity modulation with direct detection link, nonlinear distortion information is represented by a transfer function that expanded in terms of the Tyler functions.

$$P(t) = a_0 + a_1 x(t) + a_2 [x(t)]^2 + a_3 [x(t)]^3 + \dots \quad (2)$$

To convenient to extract the nonlinear signal for compensation, the expression of the recovered electrical signals after the PD is obtained by using the Eq. (2) with the Eq. (1), in which S_1 is the nonlinear distortion related to XMD, and S_2 is the distortion term related to XMD and IMD3.

$$S(t) = S_1 + S_2 A_n(t) \cos(\omega_n t + \phi_n(t)) \quad (3)$$

The nonlinear signal for compensation is obtained as following:

$$S_c(t) = S_1 * S_2^\gamma \quad (4)$$

In Eq. (4), the compensation factor γ is introduced to eliminate the XMD. By obtaining the appropriate compensation factor γ , constructing the $S_c(t)$ to feedback to the link, the XMD will be mitigated. Instead of calculating the compensation factor γ by mathematical small signal model of the link, the γ is obtained by the ANN-GA. The ANN is trained to predict the input-to-output mapping of the link, and give a predicted output value as the fitness value. Based on the fitness value, the genetic algorithm found the optimal compensation factor γ .

2.2 Seeking Compensation Factor γ Based on the ANN-GA

The process of seeking compensation factor γ based on the ANN-GA is divided into two steps, as shown in Fig. 2. Step 1: training back propagation (BP) neural network and predict the output of the link, and Step 2: seeking the γ value and the corresponding minimal XMD suppression ratio value by genetic algorithm. We do not need to derive the exact function relationship of input-output of the microwave photon link, but instead of training the BP neural network with a certain amount of input and output data of the link. Then, the trained BP neural network can predict the output of the microwave photon link according to the fitted input-to-output mapping. Use the predicted results as individual fitness values of the genetic algorithm. With the selection, the crossover and the mutation operations, the global optimal value of the XMD suppression ratio and the corresponding γ are found.

Obviously, the compensation factor γ is one of the key factor that determines the suppression ratio. In addition, another impotent impact factor is the modulator bias point. So, the compensation factor and the modulator bias point are identified as the two input variables for the link, and the XMD suppression ratio as the output. The predicted output accuracy of the neural network is key to the ability of the genetic algorithm to find the optimal XMD suppression ratio, the corresponding compensation factors and the modulator bias point. The learning capabilities of the BP neural network is closely related to its structure. Because, the memory capacity of the network, the speed of training, and the amount of response depend on the structure, which corresponds to the number of hidden layers and nodes. According to the Kolmogorov theory, a continuous function $F(x)$ in the closed intervals, can be precisely implemented with a three-layer neural network. Where the number of nodes in the input layer is M , the number of nodes in the hidden layer is $K = 2M + 1$, and the number of nodes in the output layer is N . Here we select the compensation factor and the modulator bias point as the input ($M = 2, K = 5$), and the XMD suppression ratio as the output ($N = 1$). The neural network structure is '2-5-1' type, as shown in Fig. 3.

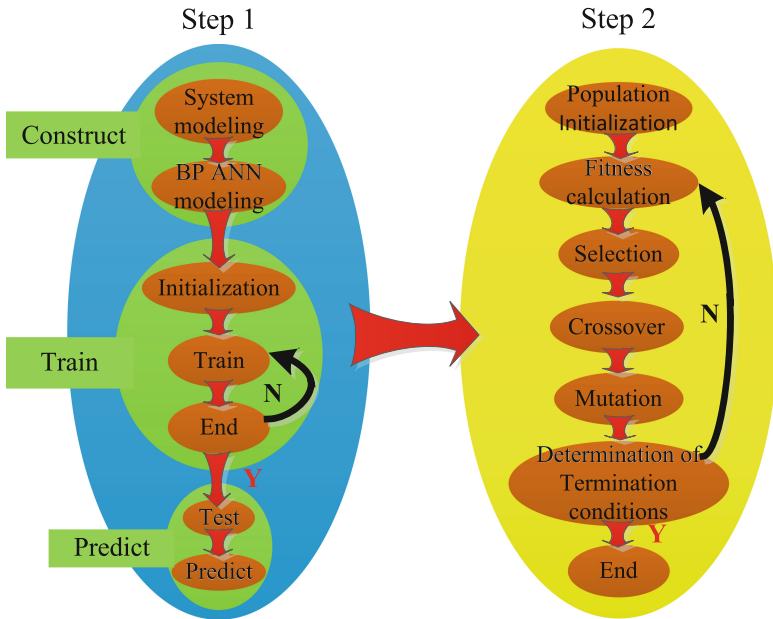


Fig. 2. The flow chart of the ANN-GA

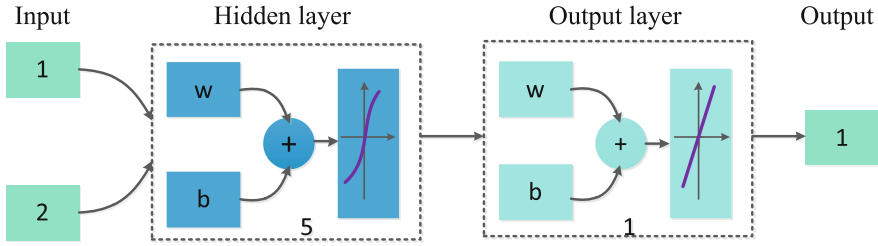


Fig. 3. The structure of the neural network

Basic operations of the genetic algorithm include the selection, the crossover, and the mutation. In the selection, the individuals which are more suited to the environment are selected to multiply the next generation from a group. The amount of reproduction is determined according to the individual’s fitness to the environment. The individual fitness value comes from the predicted value of the BP neural network. And the smaller the fitness value, the better the individual. The individual in the genetic algorithm is encoded as a real number, and the length of the individual is 2, because of only 2 input parameters for the optimization function. The probability of crossover and mutation are set as needed.

3 Simulation Results

The MDC-MWPL is simulated by MATLAB with the model shown as in Fig. 1(a). the carrier signal is a dual tone signal with the frequency interval of 5 MHz, at the frequency of 15 GHz and 15.005 GHz, respectively. The selected crosstalk signal is a dual tone signal with the frequency interval of 1.5 MHz, at the frequency of 3 GHz and 3.0015 GHz, respectively. The local oscillator signal is introduced to down-convert the carrier to the medium frequency of 80 MHz. The switching voltage of modulator, the effective responsivity of the PD, and the input optical power of the PD are set to 6 V, 0.9 A/W, and 5 dBm, respectively. The output spectrum of the link without compensation is shown in Fig. 4. As we can see, the IF signals are seriously interfered by XMD signals with the power of -63 dBm, at the frequency of 73.5 MHz, 76.5 MHz, 78.5 MHz and 81.5 MHz, respectively.

Then, the XMD compensation based on the ANN-GA is also simulated using the MATLAB. A total of 2500 sets of input and output data of the link are taken, from which 2250 sets of data are randomly selected to train the BP neural network, and 250 sets of data are used to test the fitting performance of the BP neural network. The comparison results of BP neural network prediction output and expected output are shown in the Fig. 5(a). then the error percentage of prediction κ is calculated by:

$$\kappa = (XMD_{pre} - XMD_{exp})/XMD_{exp} \tag{5}$$

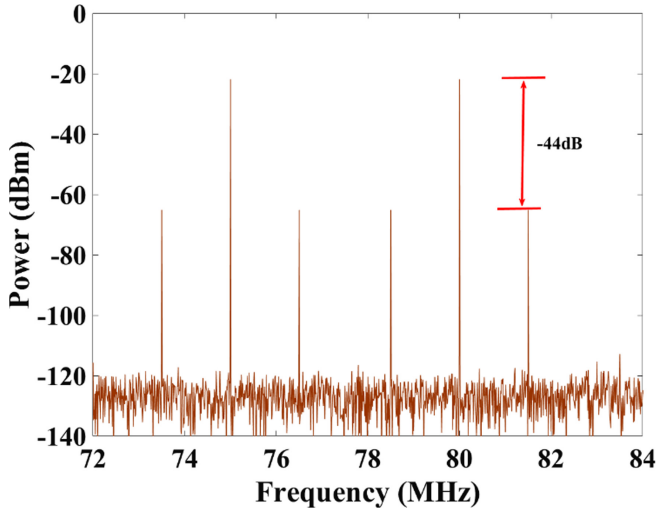
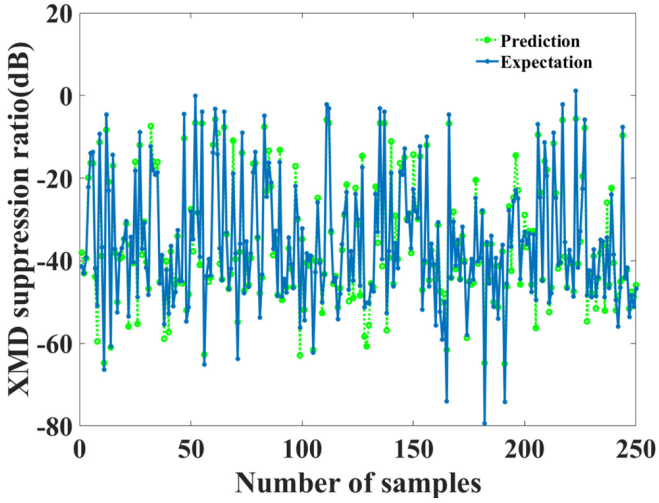


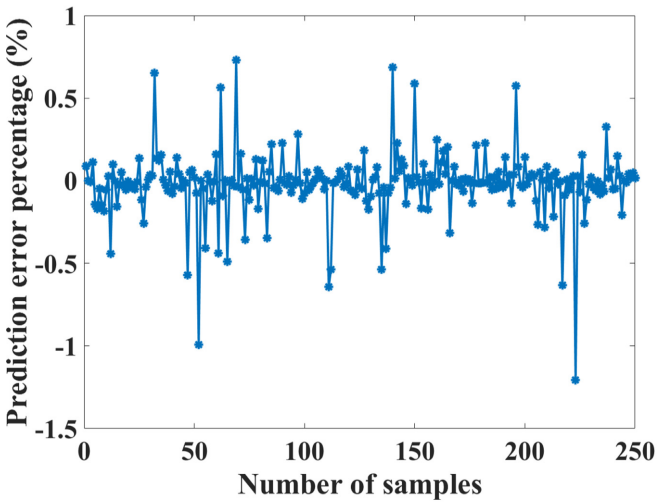
Fig. 4. The output spectrum of the link without compensation

XMD_{pre} and XMD_{exp} are prediction and expectation value of the XMD suppression ratio, respectively. From the error percentage of the prediction results, the ANN can accurately predict the output of the link. So, the predicted output can be approximately regarded as the actual output of the link.

After the BP neural network training, the genetic algorithm is used to find the compensation factor γ and the minimum value of the XMD suppression ratio. The iteration number, the population size, the crossover and the mutation probability are set to 100, 20, 0.4 and 0.2, respectively. The evolution curve of the optimal individual fitness value in the optimization process is shown in the Fig. 6(a). From the evolution curve, the fitness value of the optimal individual and the corresponding optimal individual are -65 and $[0.15, 2.6]$, respectively. When the phase bias point and the compensation factor are 0.15rad and 2.6 , respectively, the corresponding XMD suppression ratio is -65 dB. As shown in Fig. 6(b), after compensation, the power of XMD is reduced from -63 dBm to -86 dBm, which exhibits the excellent XMD mitigation performance of the proposed technique.

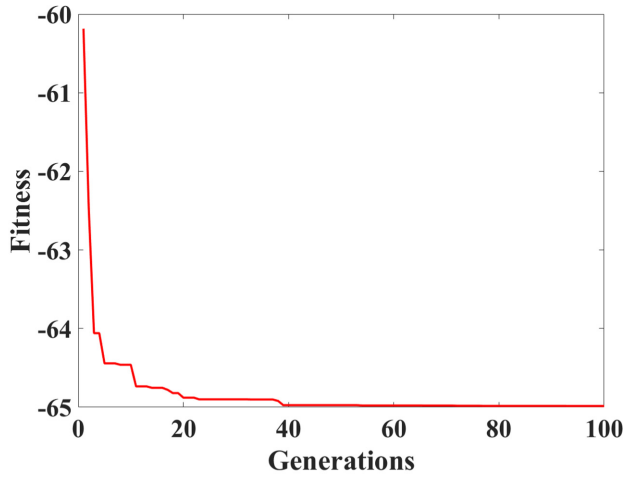


(a)

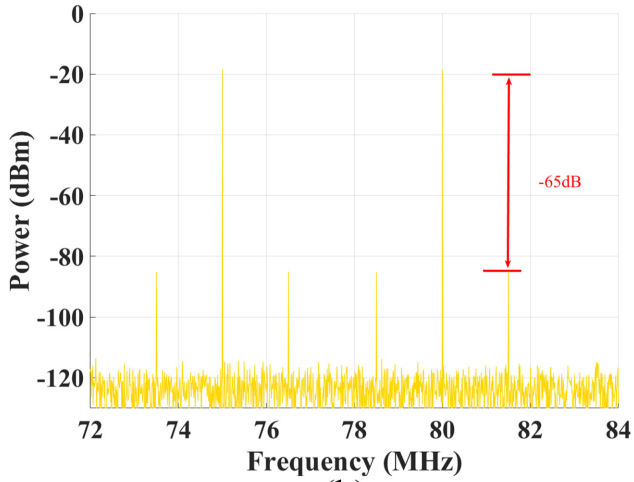


(b)

Fig. 5. The prediction of the trained ANN versus the number of samples, (a) the comparison of prediction and expectation values of XMD suppression ratio (link output), (b) the error percentage of prediction.



(a)



(b)

Fig. 6. (a) The fitness curve versus generations, (b) the spectrum of the link after XMD compensation by using the ANN-GA.

4 Conclusion

In broadband, multi-carrier, down-conversion microwave photonics link, the XMD will seriously affect the link performance, such as reducing the dynamic range of the link. The proposed technique suppresses the XMD of the link with a suppression ratio of -65 dB, based on the artificial neural network genetic algorithm. The artificial neural networks learn and predict the input-to-output mapping of the link, and provide a predicted output value as the individual fitness value of the genetic algorithm. Based on the fitness value, the optimal compensation factor γ is found by the genetic algorithm. Then, the compensation signal is extracted, and reconstructed by multiplying by the γ , and fed back to the link to eliminate the XMD. The combination of the artificial neural network and microwave photonics provides a new idea for the design of high performance microwave photonics link. Different from the traditional digital distortion compensation, the proposed technique can realize distortion compensation for any kinds of links, which is not limited to a fixed microwave photonics link and its mathematical model, improving the intelligence and flexibility of microwave photonic link linearization design.

References

1. Skeie, H., Johnson, R.V.: Linearization of electro-optic modulators by a cascade coupling of phase modulating electrodes. In: Proceedings of the SPIE, vol. 1583, pp. 153–164 (1991)
2. Brooks, J.L., Maurer, G.S., Becker, R.A.: Implementation and evaluation of a dual parallel linearization system for AM-SCM video transmission. *J. Lightwave Technol.* **11**(1), 34–41 (1993)
3. Magoon, V., Jalali, B.: Electronic linearization and bias control for externally modulated fiber optic link. In: 2020 IEEE International Topical Meeting on Microwave Photonics, pp. 145–147. IEEE (2000)
4. Childs, R.B., O’Byrne, V.A.: Multichannel AM video transmission using a high-power Nd:YAG laser and linearized external modulator. *IEEE J. Sel. Areas Comm.* **8**(7), 1369–1376 (1990)
5. Haas, B.M., Murphy, T.E.: A simple, linearized, phase-modulated analog optical transmission system. *IEEE Photon. Technol. Lett.* **19**(10), 729–731 (2007)
6. Masella, B., Hraimel, B., Zhang, X.: Enhanced spurious-free dynamic range using mixed polarization in optical single sideband mach-zehnder modulator. *J. Lightwave Technol.* **27**(15), 3034–3041 (2009)
7. Lv, Q., Xu, K., Dai, Y., Li, Y., Wu, J., Lin, J.: I/Q intensity-demodulation analog photonic link based on polarization modulator. *Opt. Lett.* **36**(23), 4602–4604 (2011)
8. Clark, T.R., Dennis, M.L.: Coherent optical phase modulation link. *IEEE Photon. Technol. Lett.* **19**(16), 1206–1208 (2007)
9. Agarwal, A., Banwell, T., Toliver, P., Woodward, T.K.: Predistortion compensation of nonlinearities in channelized RF photonic links using a dual-port optical modulator. *IEEE Photon. Technol. Lett.* **23**(1), 24–26 (2011)
10. Banwell, T., Agarwal, A., Toliver, P., Woodward, T.K.: Compensation of cross-gain modulation in filtered multi-channel optical signal processing applications. In: 2010 Optical Fiber Communication Conference, pp. OWW5. IEEE (2010)
11. Zou, X., Xu, S., Li, S., Chen, J., Zou, W.: Optimization of the brillouin instantaneous frequency measurement using convolutional neural networks. *Opt. Lett.* **44**(23), 5723–5726 (2019)

12. Ye, H., Li, G.Y., Juang, B.H.: Power of deep learning for channel estimation and signal detection in OFDM. *IEEE Wirel. Commun. Lett.* **7**(1), 114–117 (2018)
13. Khan, F.N., Fan, Q., Lu, C., Lau, A.P.T.: An optical communication's perspective on machine learning and its applications. *J. Lightwave Technol.* **37**(2), 493–516 (2019)